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Projection Pursuit Method Based on Connection Cloud Model for Assessment of Debris Flow Disasters

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ABSTRACT. A rational evaluation of the danger of debris flow disasters at the regional scale is essential for developing effective disaster prevention measures and economic planning in debris flow-prone areas. A novel projection pursuit method based on the connection cloud model and fruit fly optimization algorithm is addressed to analyze the dangerous degree of debris flow disasters at the regional scale, considering the random and fuzzy uncertainties of the projection direction vector. In this method, the connection cloud model generates the candidate projection directions around the latest optimization; these candidate projection direction vectors are screened based on set pair analysis to advance the convergence rate. Case studies and comparisons with other algorithms are further carried out to verify the validity and reliability of the proposed method. Results demonstrate that the proposed method does not require existing evaluation criteria compared to the conventional evaluation methods. It can describe the randomness and fuzziness of the projection direction vector and better find the structural characteristics of fuzzy indicators randomly distributed in the finite intervals with a quicker convergence rate.

Keywords: projection pursuit, fruit fly optimization algorithm, debris flow, connection cloud model, assessment

1. Introduction

The assessment of debris flow disasters at a regional scale is not only critical to the emergency response (Di et al., 2008; Liu et al., 2009; Chiou et al., 2015; Ouyang et al., 2019), disaster prevention and relief (Chang et al., 2017; Yin and Zhang, 2018), but also the decision-making in economic development planning (Liu et al., 2002; Liu et al., 2013). Debris flow is a sudden and complex natural disaster process affected by various uncertain factors (Chen et al., 2016). Physical and statistical approaches (Carrara et al., 2008) and numerical methods (Chang et al., 2010; Han et al., 2019) help analyze the debris flow disasters in case of lack of historical data, but these methods are not proper to represent the complicated relationship between the tragedies and the contributing variable values. They may also entail substantial uncertainties due to the high sensibility to input parameters of variability (Bregoli et al., 2015; Kang and Lee, 2018) and some assumptions used to simplify the complexity of the composition and mechanism of the debris flow (Wang et al., 2018). The multi-factor composite assessment model (Liu et al., 2002; Hürlimann et al., 2006), minimum entropy analysis (Chen et al., 2007), and geographic information system (GIS) technology (Han et al., 2007; Bregoli et al., 2015; Kim et al., 2016) have been introduced to represent the actual relationship between the debris flow phenomenon and contributing variables (Liu et al., 2006). However, previous methods are confirmatory data analysis (CDA) methods (Li, 1997). Unfortunately, the CDA method often results in the problem of the "curse of dimensionality" (Zhang and Dong, 2009). It is unsuitable for the issues of non-normal distribution or small-size samples under multiple uncertainties.

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The assessment of debris flow disasters inevitably involves the indicators of non-normal distributions and uncertain characteristics. To overcome the above limitations, many scholars used fuzzy sets theory and correlation degree method (Gan et al., 2019) associated with the selected factors and their weighting to improve the quality of assessment. Still, they cannot provide the influence degree of each element on the nonlinear behavior of debris flow disasters and rarely involve multiple uncertainties such as fuzziness and randomness. Furthermore, these methods are set up based on the existing classification standards or empirical rules, while processes with no classification standards are relatively few. Consequently, there are some limitations in assessing debris flow disasters using the above methods of classification standards because the classification standard of debris flow disasters often varies in different areas, and its establishment is reasonably complicated.

Recently, some robust approaches (Wang, 2000; Liu et al., 2006; Yuan and Zhang, 2006; Chang and Chien, 2007; Liang et al., 2012; Liu et al., 2013; Qian et al., 2016; Xu et al., 2017;

Banihabib et al., 2020) have been further discussed to eliminate the high relativity existing in their results for the improvements of assessment reliability (Li et al., 2019). These methods have improved the quantitative assessment of debris flow disasters to some extent. However, they are hard to explore the inherent structural characteristics of the high-dimensional data and to depict the multiple uncertainties of indicators. Obviously, because of the complex nature of debris flow and composite indeterminacy of influenced factors (Zhang et al., 2011), it is not easy to precisely understand the mechanism and forecast their occurrence. Sometimes different results may be obtained using these methods with varying classification standards despite the exact regional location of debris flow. Consequently, the projection pursuit (PP) method put forward by Friedman and Turkey (1974) is applied gradually to reveal the structural characteristics of debris flow data from a testing perspective (Wang et al., 2002). This PP method can overcome the defect of the "curse of dimensionality" of the CDA method and automatically express nonliner characteristics of high-dimensional problems (Xiao and Chen, 2012) to the extent. Still, the issue of projection direction determination has not been well solved up to the present because the occurrence and development of actual debris flow are of randomness and fuzziness. To this end, some evolutionary algorithms and swarm intelligence methods, including the shuffled frog leaping algorithm (Wang et al., 2009), particle swarm optimization (Xu and Xu, 2010), differential evolution method (Niu et al., 2015), grey wolf optimization method (Yu and Lu, 2018), and moth-flame optimization (Liu et al., 2019), was introduced to pursue the optimal PDV. These methods can get more benefits than those by the traditional gradient or polynomial optimization methods. However, these algorithms rarely consider multiple uncertainties.

Luckily, the fruit fly optimization algorithm (FOA) developed by Pan (2012) provides a new way to quickly find the optimal solution of the optimization problem because it has generalizability and the advantages of easy implementation and understanding and a reasonable convergence rate. Today, the algorithm has been successfully applied in various fields (Tian and Li, 2019; Wang et al., 2019; Peng et al., 2020; Xiong and Liang, 2021). Of course, the algorithm provides a powerful tool to find the optimal PDV of the PP method. Nevertheless, the classic FOA often adopts a fixed search range to pursue the optimal individual. It may result in the local optima problem when the optimum is far from the origin (Tian and Li, 2019). In addition, the traditional FOA may be unable to analyze the case where the independent variable takes a negative value or 0. It is easy to fall into early maturity convergence for the optimal solution away from the original position. Up to the present, reports on the FOA rarely focused on the fuzziness and randomness of the PDV. So to enhance the global optimization capability of the FOA, some enhanced FOAs such as the multi-swarm fruit fly optimization algorithm (MFOA) (Yuan et al., 2014), the improved fruit fly optimization algorithm (IFOA) using an adaptive search scope (Pan et al., 2014; Tian and Li, 2019), and chaotic fruit fly optimization algorithm (CFOA) (Lei et al., 2014; Mitić et al., 2015) were proposed to enhance the performance based on the improvements of the search radius, generation mechanism of candidate source, and flight strategy (Pan et al., 2014; Zhang et al., 2016; Zhang et al., 2020). These improved FOAs have enhanced the simulation of the foraging randomness of fruit flies and have avoided being trapped in local premature to some extent. However, they cannot reflect the fuzzy characteristic of individual foraging behavior and the fuzziness at the bounds, which may decrease the search efficiency and the ability to express data structure with uncertainties. Hence, the assignment of optimal PDV using the FOA and previous improved FOAs cannot simultaneously describe ambiguous and arbitrary characteristics. It is a great demand for developing an improved FOA to enhance the performance of the PP evaluation method for high-dimensional problems under multiple uncertain environments.

The fruit fly swarm's foraging process dynamically updates the source position based on the perceived smell concentration in the conventional FOA. Still, the site of each fruit fly and its decision of smell concentration are random and ambiguous in the finite interval. Hence, the individual search range and direction are of randomness and fuzziness when flying to the optimal individual. To simultaneously characterize the randomness and fuzziness of foraging behaviors of fruit fly swarm, Wu et al. (2015) used a normal cloud generator to depict the updated location of individuals instead of the uniform random distribution in the osphresis stage. Nevertheless, it ignores the interval characteristic of the arbitrary and fuzzy uncertainties and cannot accurately express the fuzziness at the bounds. Fortunately, the connection cloud model (CCM) present by Wang and Jin (2017) can depict the changing tendency of the jumps and the certainty-uncertainty relationship by identity, discrepancy, and contrary views. Thus, CCM is available to represent the actual characteristic of individual foraging processes. A novel CCM-based fruit fly optimization algorithm (CCMFOA) is introduced here to seek the optimal PDV for the indicators with multiple uncertainties in the restricted intervals and improve the global and local searching performance of the PP method for the assessment of debris flow disasters.

As follows from the previous discussion, debris flow disasters on a regional scale are of nonlinear characteristics and multiple uncertainties. Earlier studies on the FOA were rarely focused on describing the fuzziness and randomness of finding the optimal PDV (Lin et al., 2012; Xu et al., 2017; Banihabib et al., 2020), while the CCM can handle these problems (Wang et al. 2020; Wang et al., 2021). To simultaneously consider the fuzzy and random uncertainties of the PDV in the finite intervals, it is a tremendous demand for enhancing the performance of the PP method using an improved FOA based on the connection cloud model.

Given the multiple uncertainties of debris flow evaluation, a novel PP method using CCM-based FOA is discussed to analyze the dangerous degree of debris flow. To better pursue the optimal PDV, the generation mechanism of the new PDV is first strengthened by the set pair analysis. Namely, the identity-discrepancy-contrary (IDC) rule of set pair analysis is discussed to screen the candidate PDV. Meanwhile, the mechanism "picks the best of the best" is adopted to attain the goal of the candidate solution. The validity and feasibility of the proposed PP evaluation method were further confirmed by case studies and comparative analysis with other methods. The improved FOA presented here is helpful to improve the generation mechanism and search rate of the optimal PDV, and is a balanced algorithm of the global searching capability and local acceptable optimization efficiency. The PP method with a quicker osphresis foraging process offers the opportunity to improve the local optimization capability and effectively depict the random and fuzzy uncertainties of individual search performance and decision. It will be helpful to apply the PP method to the assessment of debris flow disasters.

2. Methodology

2.1. Projection Pursuit

The PP method is an exploratory data analysis (EDA) method for handling non-normal and high-dimensional data problems. Its basic idea is to project high-dimensional data onto a low-dimensional space to represent specific features concerning a projection index function and the objective projection function. Then analyze the structural characteristics of original high-dimensional data with the obtained projection scores to scale the possibility of a specific structure. The critical point in the PP method is to pursue the optimal PDV, which can effectively describe the structural features of high-dimensional data. However, it is a complex work for the small size of samples under uncertain environments with complicated topology and numerous uncertainty factors. Hence, the connection cloud model and set pair analysis are introduced here to improve the FOA algorithm and pursue the optimal PDV considering the randomness and fuzziness of the individual PDV in the finite interval.

2.2. Connection Cloud Model-Based FOA (CCMFOA)

From the above discussion, variables in the normal cloud model should obey the normal distribution in the infinite interval; this may not be consistent with the actual distribution of the variables and may limit the application extent. However, the CCM overcomes this defect and can depict the uncertain characteristics in the finite intervals (Wang and Jin, 2017; Wang et al., 2020). So the CCM provides a powerful tool for the characterization of the uncertainty foraging behavior of the fruit fly swarm and the changing tendency at the bounds from three aspects of identity, discrepancy, and contrary. The CCM is defined as follows.

Let C be a qualitative concept in the domain X of finite interval. If numerical value $x \in X$ is a random implementation of concept C, then the quantitative description of x belonging to the concept C is:

$$\mu = \exp\left(-\frac{9}{2}\left|\frac{x - Ex}{3y}\right|^{\theta}\right) \tag{1}$$

where μ represents the connection degree, $\mu \in [0, 1]$. y and x are random numbers obeying the normal distribution N (En, He^2) and N (Ex, y^2), correspondingly. Ex, En, He, and θ are the expectation, entropy, hyper entropy, the order of the distribution density function for the numerical characteristics of the CCM, respectively. They are given as:

$$Ex = \frac{L_{max} + L_{min}}{2} \tag{2}$$

$$En = \frac{\lambda}{3} \tag{3}$$

$$He = \beta \tag{4}$$

$$\theta = \frac{\ln\left(\frac{\ln 4}{9}\right)}{\ln\left|\frac{l - Ex}{3En}\right|} \tag{5}$$

where L_{max} and L_{min} denote the upper and lower limitations of the interval, respectively; β represents the fuzzy degree; l represents the indicator value at the connection degree of 0.5; λ is the width of the left or right half branch of cloud.

3. Development of the PP Method

3.1. Basic Principle

The basic principle of the PP method using the CCMFOA for the assessment of debris flow disasters is presented as follows: Firstly, standardize measured values of indicators, and initialize the PDV and parameters of the CCMFOA. Next, set up the projection index function and the projection objective model. Then, generate the candidate PDV around the latest optimal PDV by the connection cloud generator and preselect the PDV based on the set pair analysis. Namely, the expectation Ex and the entropy En of the numerical characteristics are used to depict the randomness and fuzziness of the optimal PDV and search range in the smelling stage. And to embody the greedy strategy for the generation mechanism of the PDV, the IDC relationship between the candidate PDV and the optimal PDV obtained from the latest optimization iteration is also investigated based on the theory of set pair analysis. Moreover, adaptive entropy with a specific number of iterations is adopted to enhance the local convergence speed. Then next, pursue the optimal PDV according to the projection index function and the projection objective model. Finally, measured data of debris flow disasters are projected into a low-dimensional subspace to investigate the data structure based on the optimal PDV found.

3.2. Evaluation Procedure

The assessment procedures of debris flow disasters with the PP method coupled with the CCMFOA are illustrated in Figure 1. And the detailed process consists of eight steps as follows.

Step 1: Determine the assessment index system of debris flow disasters and standardize measured values of indicators. Index selection profoundly influences the assessment of debris flow disasters. Based on the understanding of generation conditions of debris flows in the existing reports, case studies, and

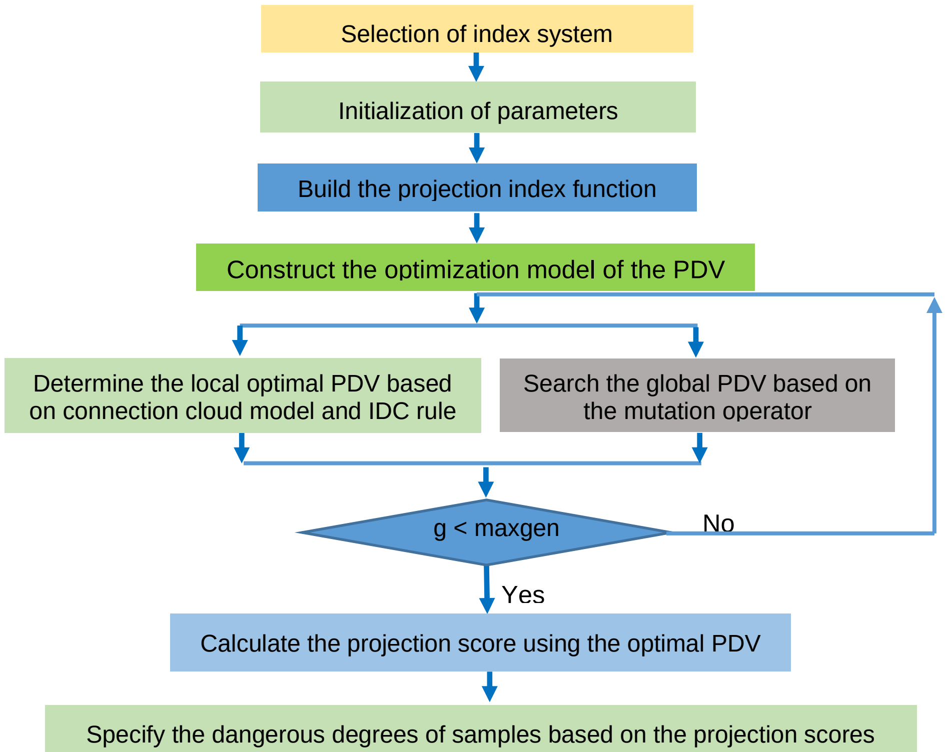

Figure 1. Flowchart of the PP method based on the CCMFOA for the assessment of debris flow disasters.

analyses, variables including topographic slope, formation lithology, channel density, annual average rainfall, and seismic intensity are often selected as the evaluation factors for the dangerous degree of debris flow (Liu and Tang, 1995; Liu et al., 2002; Liu et al., 2006; Liang et al., 2012; Yin and Zhang, 2018).

The measured values of indicators with various fields should be normalized to reduce the impacts of different dimensions among indicators. For the benefit indicator, the normalization model is:

$$x_{ij}^{*} = \left(x_{ij} - x_{min}^{j}\right) / \left(x_{max}^{j} - x_{min}^{j}\right) \tag{6}$$

where, x_{ij}^{*} and x_{ij} denote the normalized and measured values of index j of sample i, respectively; x_{max}^{j} and x_{min}^{j} are the maximum and minimum values of the evaluation index j. While for the cost indicator, the corresponding model is given as:

$$x_{ij}^{*} = \left(x_{max}^{j} - x_{ij}\right) / \left(x_{max}^{j} - x_{min}^{j}\right) \tag{7}$$

Step 2: Initialize the PDV and parameters of the CCMFOA:

$$X_{ij} = LB_j + \left(UB_j - LB_j\right) \cdot rand() / 2 \tag{8}$$

where X_{ij} is the initial PDV; LB_j and UB_j denote the lower and upper bounds of index j; *rand*() represents a function that produces a random number obeying the standard uniform distribution on the open interval (0, 1).

Step 3: To characterize the structural features of the measured data and represent the structural characteristics of data and pursue the optimal PDV, establish a proper projection index function to obtain the local projection points as dense the group points as scattered as possible. Here, a linear projection index function is used to specify the projection cores scores, its mathematical model is written as:

$$Q(\boldsymbol{\alpha}) = S(\boldsymbol{\alpha}) \cdot D(\boldsymbol{\alpha}) \tag{9}$$

$$S(\alpha) = [\sum_{i=1}^{n}\left(Z_i(\alpha) - \bar{Z}(\alpha)\right)^2 / (n-1)]^{0.5} \tag{10}$$

$$D(\alpha) = \sum_{i=1}^{n}\sum_{k=1}^{n}\left(R - r_{ik}\right) \cdot I(R - r_{ik}) \tag{11}$$

$$R = \psi \cdot S(\alpha) \tag{12}$$

$$r_{ik} = \left|Z_i(\alpha) - Z_k(\alpha)\right| \tag{13}$$

$$Z_i(\alpha) = \sum_{k=1}^{m} \alpha_p x_{ik}^{*} \tag{14}$$

where $\boldsymbol{\alpha}$ denotes a projection direction vector. $Q(\boldsymbol{\alpha})$ is the projection index function. $S(\boldsymbol{\alpha})$ represents the dispersion characteristics of projection scores $Z_i(\boldsymbol{\alpha})$ obtained based on the PDV $\boldsymbol{\alpha}$. $D(\boldsymbol{\alpha})$ denotes the local density of low-dimensional data points. $\bar{Z}(\alpha)$

denotes the mean value of projection scores. R is the window radius of the local thickness. Ψ is a coefficient; r_{ik} (i = 1, 2, …, n; k = 1, 2, …, n) denotes the distance. I represents a unit leap function that takes 1 when R is greater than or equal to r_{ik}; otherwise, it takes 0.

Step 4: Build an optimization model of the PDV. According to the projection index function, projection scores of samples only vary with the PDV for the given indicator values. The optimal PDV can best depict the structural feature of high-dimensional data. The determination of the optimal PDV is regarded here as a problem of maximizing the objective projecttion function. The corresponding process is written as:

$$\begin{cases} max\left[Q(\boldsymbol{\alpha})\right] \\ s.t. \quad \sum_{j=1}^{m} \alpha_j^2 = 1 \end{cases} \tag{15}$$

where α_j denotes the j^{th} projection direction.

Step 5: Generate the candidate PDV using the CCM. Numerical characteristics of the CCM were utilized here to depict the randomness, fuzziness, and stability of the candidate PDV. Namely, the optimal PDV obtained from the latest iteration is characterized by the expectation Ex of the CCM, and the random number y is used to express the random and fuzzy characteristics of the individual search radius. The new PDV is randomly generated near the expectation Ex using numerical characteristics' parameters of entropy y and hyper entropy He. The entropy En is also changed dynamically with the iteration number to increase the algorithm's convergence speed. Its mathematical model is:

$$En = \left(1 - \frac{g}{maxgen}\right)^{\zeta} \cdot \left[2 \times rand() - 1\right] / 6 \tag{16}$$

where ζ is the coefficient of adaptive control; g and $maxgen$ are the g^{th} iteration number and maximum iteration number, respecttively.

Step 6: Screen the candidate PDV with the IDC analysis. The theory of set pair analysis (SPA) proposed by Zhao (2000) is introduced here to improve the efficiency of finding the optimal PDV and the generation mechanism of PDV. Namely, the connection degree of a set pair, consisting of the candidate PDV and the latest optimum PDV of fruit fly swarm, is calculated with Equation (1) to analyze the IDC relationship with the theory of set pair analysis (Wang and Jin, 2017). Herein, the identity and contrary relationships for the assessment of debris flow disasters are as follows: an identity relationship between the candidate PDV and the optimal PDV of the swarm is defined when the corresponding connection degree is more significant than 0.5. In contrast, a contrary relationship is determined when the connection degree is less than 0.5. The SPA between the candidate PDV and the latest optimal PDV can be illustrated in Figure 2.

The candidate PDV of an identity relationship with the newest optimal PDV of fruit fly swarm can be directly used to calculate the projection score. In contrast, the candidate PDV of a contrary relationship may not meet the candidate generation mechanism of the PDV and should be regenerated before the complex calculation. It can promote the faster aggregation to the optimal PDV obtained by the most recent iteration and enhance the FOA algorithm's convergence speed. Thus, in the CCMFOA, the candidate generation mechanism based on the CCM and the set pair analysis can reflect the randomness and fuzziness of individual decision-making of smell concentration and enhance search capability relative to the basic FOA and other improved FOAs.

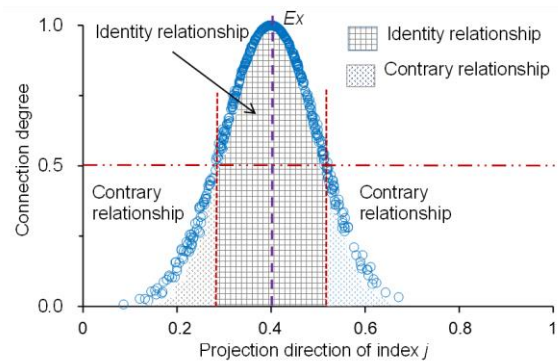

Figure 2. IDC relationship between the candidate PDV and the latest optimal PDV.

Step 7: Conduct the iteration calculation to determine the optimal PDV with the PP method and CCMFOA. The corresponding pseudo-code for finding the optimal PDV using CCMFOA is listed in Figure 3.

Step 8: Calculate projection scores of samples with the obtained optimal PDV, and then analyze debris flow disasters according to the projection score.

4. Case Study

4.1. Case 1

4.1.1. Data

Case selection is of great importance for the reliability validation of the model. A case reported by Liu and Tang (1995) was utilized here to confirm the validity and reliability of the proposed method. This instance has been commonly used for validation analyses of new models in China (Wang, 2000; Liu et al., 2002; Wang et al., 2002; Liu et al., 2006; Xu et al., 2017). The results from the neural network method and the PP methods based on other improved FOAs and RAGA were conducted further. This case chose eight indicators (the spatial density of debris flow gullies C_1, the flood hazard frequency C_2, the weathering degree of rock C_3, the variation coefficient of the mean annual precipitation C_4, the fault density C_5, the average day of rainfall more than 25 mm by ten years C_6, the percentage of land area with a slope greater than 25° of land area C_7, and the percentage of cultivated land with a slope greater than 25° of total cultivated land C_8) to analyze the dangerous degree of

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Algorithm 1: Optimization algorithm of finding the optimal PDV based on the CCMFOA.
Initialize NP, p, δ, maxgen, He, ζ;
for i = 1: NP
  for j = 1: m
    α1 = rand (); Randomly generated projection direction vector α1 of NP × p by uniform distribution
  end for
end for
[Q α Z] = projection_pursuit(α1, x, δ);
Smell = Q;
[bestSmell bestindex] = max(Smell);
Smellbest = bestSmell;
α(j, 1) = α;
for g = 1: maxgen
  for j = 1: m
     Ex(j, g) = α(j, k);
     Adaptive adjustment of En;
     K = 1;
     while k <= NP
       Produce a random number y, obeying the normal distribution N(En, He^2);
       Produce a random number α2, obeying the normal distribution N[Ex(j, g), y^2];
       k = { k+1   for μ ≥ 0.5
           { k     otherwise ;
     end while
  end for
[Q2 α Z2] = projection_pursuit(α2, x, δ);
Smell2 = Q2;
[bestSmell2 bestindex2] = max(Smell2);
end for
```

Figure 3. Pseudo-code for finding the optimal PDV using the CCMFOA.

Table 1. Index Values of Samples of Case 1 (Liu and Tang, 1995)

Samples	County	Indicator							
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
1	Wenchuan	24.76	23.08	1.85	0.78	95.38	1.28	31.72	32.69
2	Lixian	42.02	57.14	1.80	0.68	18.94	0.93	4.56	41.90
3	Maoxian	28.69	42.86	1.89	0.78	151.85	1.45	8.32	30.82
4	Heishui	23.92	25.00	1.79	0.77	20.34	2.68	13.49	44.54
5	Songfan	7.88	14.29	1.76	0.71	65.97	1.40	19.72	61.56
6	Maerkang	5.99	16.67	1.69	0.86	8.19	2.50	1.63	76.01
7	Rangtang	5.45	16.67	1.67	0.93	8.11	1.83	1.33	91.66
8	Jinchuan	40.99	57.14	1.73	0.89	12.59	1.38	36.89	65.91
9	Xiaojin	19.08	14.29	1.82	0.83	2.82	1.34	22.66	48.45

Table 2. Optimal PDVs Obtained from Different Algorithms in Case 1

Algorithm	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
RAGA	0.897	0.772	0.699	0.209	0.160	0.044	0.751	0.109
IFOA	0.472	0.526	0.122	0.135	0.586	0.061	0.346	0.000
CFOA	0.374	0.831	0.049	0.103	0.293	0.157	0.155	0.148
CCMFOA	0.405	0.812	0.011	0.111	0.394	0.091	0.008	0.041

debris flow disasters. The spatial density of debris flow gullies refers to the regional magnitude and frequency of the debris flow disasters. The weathering degree of rock and the fault density represents geological conditions of debris flow formation. The percentage of land area with a slope more significant than 25° of the land area is related to the geomorphologic state and denotes the potential energy of debris flow disasters. The flood hazard frequency is a hydrological index relating to the possible number of debris flow occurrences. The variation coefficient of the mean annual precipitation represents a meteorological variable. The average day of rainfall more than 25 mm by ten years is a water volume index for debris flow formation. And the percentage of cultivated land with a slope greater than 25° of total cultivated land denotes the influence of human activity on debris flow activities. Their relative degree analyses to the dangerous degree can be found in references (Liu and Tang, 1995; Liu et al., 2002). Index values of samples of case 1 are listed in Table 1.

Table 3. Comparisons of Projection Scores among Different Algorithms in Case 1

Algorithms	1	2	3	4	5	6	7	8	9	10
RAGA (Wang and Jin, 2002)	0.903	1.374	1.374	0.908	0.561	0.253	0.244	1.787	0.897	1.021
IFOA	1.197	1.197	1.499	0.768	0.586	0.292	0.292	1.499	0.586	1.071
CFOA	0.806	1.320	1.252	0.753	0.397	0.421	0.420	1.582	0.418	1.036
CCMFOA	0.705	1.276	1.276	0.606	0.265	0.265	0.265	1.379	0.265	1.003

Table 4. Ranks of Debris Flow Disasters Obtained with Different Methods

Samples	Country	ANN (Wang, 2000)	RAGA (Wang et al., 2002)	IFOA	CFOA	CCMFOA
1	Wenchuan	III	III	III	III	III
2	Lixian	IV	IV	III	IV	IV
3	Maoxian	IV	IV	V	IV	IV
4	Heishui	III	III	II	III	III
5	Songfan	II	II	II	II	II
6	Maerkang	I	I	I	II	II
7	Rangtang	II	II	I	II	II
8	Jinchuan	V	V	V	V	V
9	Xiaojin	II	II	II	II	II

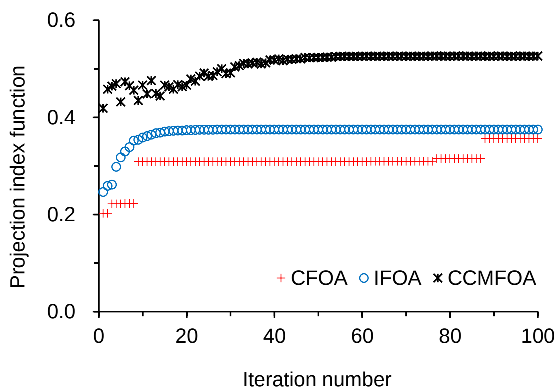

Figure 4. Optimization process along with iteration number in case 1.

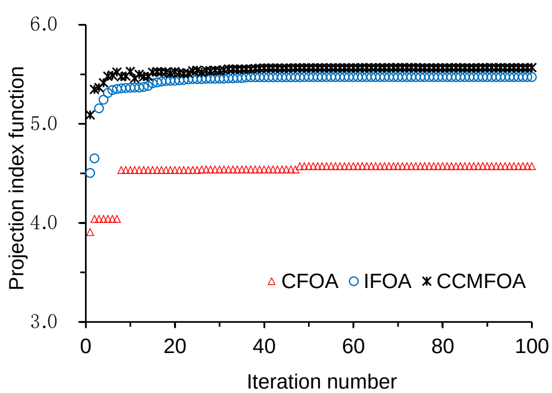

Figure 5. Optimization process along with iteration number in case 2.

4.1.2. Model Implementation

According to the procedure in Section 3, the optimal PDV $\boldsymbol{\alpha}$ = (0.405, 0.812, 0.011, 0.111, 0.394, 0.091, 0.008, 0.041) in case 1 is obtained with the population size of 80, the iteration number of 100 and the adaptive control coefficient ζ of 7. The corresponding maximum value of the projection index function $Q(\boldsymbol{\alpha})$ is 0.53. Projection scores of samples based on the corresponding PDVs (Table 2) obtained from the RAGA, IFOA, CFOA, and CCMFOA are listed in Table 3.

4.1.3. Analysis of Results

According to the aggregation distribution of projection sores among samples, the ranks of debris flow disasters are specified as five levels from very low (I), low (II), moderate (III), significant (IV), to high (V). Grades of the dangerous degree for samples obtained from different methods for case 1 are listed in Table 4. It is observed in Table 4 that the orders from small to large for projection scores obtained by the CCMFOA were samples 5, 7, 9, 6, 4, 1, 10, 3, 2, and 8. The dangerous degrees of samples 5, 6, 7, and 9 were low II. The grade of samples 1, 4, and 10 were moderate III. Samples 2 and 3 were rated as significant IV; and sample 8 was specified as high V, respectively. Results from the PP method were broadly consistent with those of the neural network method except sample 6. These results indicate that the proposed way is efficient and feasible. The PP method can directly describe the information of multiple variables and the dangerous degree of debris flow disasters with one-dimensional variables. The neural network behaves like a black box effect and cannot directly correlate between indicators and ratings.

4.2. Case 2

4.2.1. Data

There are no clear and unified classification standards for the dangerous degree of debris flow hazard so far. Different indicator systems may lead to changes in results obtained by the same method. Herein, data from the literature (Wang, 2009; Li et al., 2021) named case 2 was consequently added to verify the proposed model's validity further. In case 2, 39 debris flow in Beichuan were selected to confirm the feasibility and rationality of the proposed method. Beichuan County is located in the subtropical humid monsoon climatic zone in Sichuan, China. High debris flows occur in the loose Quaternary layers in July-September because the rainfall is concentrated chiefly in the summer. Loose source material reserves (10^3 m^3), S_1, basin area (km^2), S_2, drainage density (km^{-1}), S_3, basin relative relief (km), S_4, shifting bed proportion (%), S_5, main channel length (km),

S_6, and once in 50 years of scales (10^3 m^3), S_7 were chosen as evaluation indicators. The measured values of indexes are listed in Table 5. Ranks of debris flow disasters are also specified into five levels from very low (I), low (II), moderate (III), significant (IV), to high (V). Dangerous degrees and projection scores of samples identified from the proposed model and comparisons with other methods for case 2 were listed in Tables 6 and 7.

Table 5. Index Values of Samples for Case 2 (Wang, 2009; Li et al., 2021)

Samples	S_1	S_2	S_3	S_4	S_5	S_6	S_7
1	0.04	2.5	19.32	1.60	0.48	2.06	58.54
2	39.04	13.9	21.85	1.40	0.50	4.03	200.47
3	79.50	4.5	15.89	0.98	0.64	3.35	55.44
4	104.5	1.8	28.17	1.04	0.86	1.38	56.29
5	50.20	1.9	25.68	1.10	0.48	1.36	62.95
6	2.40	2.4	18.63	1.14	0.23	1.78	60.22
7	1500.00	1.6	44.06	1.12	0.61	3.32	16.20
8	242.00	0.5	18.60	0.46	0.84	0.73	20.06
9	160.70	0.8	17.38	0.66	0.72	1.09	24.29
10	4.80	4.6	21.33	0.86	0.54	1.99	106.92
11	73.20	21.8	21.67	2.04	0.42	7.82	168.19
12	109.30	23.2	23.24	2.30	0.61	7.49	200.42
13	60.00	3.5	22.94	1.24	0.65	2.25	72.93
14	70.60	0.7	16.29	0.96	0.61	1.43	16.26
15	163.32	18.7	22.60	1.68	0.76	5.91	186.55
16	378.24	21.4	24.07	1.50	0.76	7.42	158.73
17	15.55	2.7	23.33	1.22	0.45	2.89	38.10
18	54.00	2.6	27.12	1.26	0.41	3.13	33.18
19	107.30	0.6	16.67	0.67	0.73	0.99	19.30
20	106.50	0.3	10.67	0.52	0.76	0.66	12.64
21	3.36	0.7	27.86	0.55	0.47	2.09	8.30
22	4.13	2.8	18.79	1.00	0.47	2.35	49.16
23	12.14	0.5	18.40	0.92	0.52	1.15	13.99
24	120.08	1.8	19.56	1.04	0.89	1.35	58.13
25	15.98	3.1	20.10	0.84	0.51	2.54	47.42
26	30.00	3.5	21.74	0.82	0.75	1.80	85.51
27	114.00	24.6	20.84	1.22	0.64	8.10	158.15
28	14.26	2.8	20.82	1.12	0.70	1.56	85.73
29	33.00	4.1	19.63	1.09	0.46	3.64	46.02
30	900.03	22.2	22.05	1.70	0.44	11.36	99.78
31	210.00	3.6	21.25	1.20	0.96	3.12	49.03
32	485.00	2.5	21.80	1.00	0.81	1.97	53.26
33	931.24	23.1	21.34	1.20	0.66	9.88	111.81
34	12.21	4.0	18.98	1.03	0.53	2.56	68.76
35	98.50	22.7	26.04	1.86	0.76	7.66	175.78
36	67.20	2.5	18.12	1.02	0.83	1.32	89.14
37	93.30	2.8	21.36	1.30	0.78	2.75	43.33
38	135.57	26.4	21.93	1.80	0.67	8.46	184.61
39	14.66	2.8	29.96	1.34	0.82	2.29	55.32

4.2.2. Evaluation Results

Similarly, optimal PDVs for case 2 were achieved as listed in Table 8 by the CCMFOA and other FOAs with the same parameters (NP = 80, $maxgen$ = 100, and ζ = 7) as case 1. The corresponding maximum value of the projection score obtained by the proposed method is 1.71 in case 2. Related projection scores obtained from the IFOA, CFOA, and CCMFOA are depicted as shown in Table 7.

As expected, the evaluation results of case 2 obtained by the proposed method did well with those of the PP methods based on other FOAs, as listed in Table 6. These results and comparisons indicate that the evaluation method proposed here has good stability and reliability.

Table 6. Ranks of Debris Flow Disasters Obtained with Different Methods for Case 2 (Wang, 2009)

Samples	Debris flow gully	Multi-factor composite assessment model	IFOA	CFOA	CCMFOA
1	Caimazigou	III	III	III	III
2	Shuxuegou	IV	IV	IV	IV
3	Jinlongcun	III	III	III	III
4	Wangjiashangou	III	III	III	III
5	Chenjiabaogou	III	III	III	III
6	Pijialianggou	III	III	III	III
7	Xishanpogou	III	III	III	III
8	Renjiapinggou	II	II	II	II
9	Mofanggou	II	II	II	II
10	Piankouxiang	III	III	III	III
11	Xinyegou	IV	IV	IV	IV
12	Qinglingou	IV	IV	IV	IV
13	Subaohegou	III	III	III	III
14	Shuligou	II	II	II	II
15	Tianbaigou	IV	IV	IV	IV
16	Sibanpinggou	IV	IV	IV	IV
17	Sunjiagou	III	III	III	III
18	Chayuanlianggou	III	III	III	III
19	Hanjiashangou	II	II	II	II
20	Baiguoshugou	II	II	II	II
21	Weigou	II	II	II	II
22	Madiwangou	III	III	III	III
23	Huangjiawangou	II	II	II	II
24	Jiangjiagou	III	III	III	III
25	Liujiagou	III	III	III	III
26	Daokaimengou	III	III	III	III
27	Huangtulianggou	IV	IV	IV	IV
28	Shuangminzigou	III	III	III	III
29	Shupinggou	III	III	III	III
30	Dengjiacungou	IV	IV	IV	IV
31	Qushanzhengou	III	III	III	III
32	Wanjiayangou	III	III	III	III
33	Chenjiabagou	IV	IV	IV	IV
34	Tudilianggou	III	III	III	III
35	Chanzipinggou	IV	IV	IV	IV
36	Shangyantaigou	III	III	III	III
37	Shuanyigou	III	III	III	III
38	Yangjiawangou	IV	IV	IV	IV
39	Zhaojiawangou	III	III	III	III

4.3. Comparisons and Discussions

The corresponding values of projection index function versus iteration numbers were given in Figures 4 and 5. Projection scores of samples were illustrated in Figures 6 and 7, and Tables 3 and 7. Optimal PDVs obtained with different algorithms were listed in Tables 2 and 8.

Table 7. Comparisons of Projection Scores among Different Algorithms for Case 2

Samples	IFOA	CFOA	CCMFOA
1	0.437	0.469	0.434
2	1.196	1.204	1.174
3	0.442	0.493	0.456
4	0.346	0.423	0.342
5	0.361	0.399	0.340
6	0.362	0.371	0.344
7	0.437	0.629	0.443
8	0.085	0.161	0.106
9	0.137	0.197	0.153
10	0.535	0.564	0.519
11	1.538	1.544	1.527
12	1.697	1.714	1.691
13	0.478	0.530	0.474
14	0.155	0.202	0.168
15	1.401	1.438	1.401
16	1.440	1.498	1.450
17	0.376	0.418	0.364
18	0.387	0.435	0.367
19	0.109	0.166	0.126
20	0.032	0.084	0.064
21	0.131	0.180	0.106
22	0.346	0.379	0.342
23	0.129	0.165	0.130
24	0.327	0.398	0.344
25	0.340	0.379	0.334
26	0.437	0.489	0.434
27	1.483	1.501	1.483
28	0.446	0.493	0.444
29	0.437	0.478	0.434
30	1.492	1.592	1.524
31	0.447	0.542	0.473
32	0.376	0.472	0.399
33	1.427	1.529	1.466
34	0.447	0.483	0.444
35	1.570	1.605	1.565
36	0.422	0.480	0.434
37	0.401	0.472	0.414
38	1.702	1.720	1.703
39	0.444	0.517	0.434

It was viewed in Figures 4 and 5 that curves of projection index function obtained from the proposed method were higher than those obtained from other FOAs, indicating that the presented method can get a relatively good optimal solution under the existing projection target function. Namely, both the projecttion index function value of the CCMFOA in cases 1 and 2 were the greatest. Maximum amounts of projection index obtained from the proposed model in case 1 were about 48 and 40% higher than those of the CFOA and IFOA with the same initial PDV. Moreover, projection scores changed with different algorithms despite the same rating because they were derived respectively from the various optimal PDVs. It shows that the optimization of the PDV is vital for assessing debris flow disasters with the PP method. In addition, it was seen in Figure 6 and 7 that the projection scores obtained from CFOA deviated from those from the proposed model and the IFOA model. The number of iterations in case 1 to determine the optimal PDV was 57, 27, and 85 of the CCMFOA, IFOA, and CFOA, respectively. The IFOA reached the optimal PDV most quickly, and its search speed was about 2.1 and 1.1 times faster than those of the CFOA and CCMFOA in case 1, respectively, but its projection index function value was lower than that of the CCMFOA. These suggest that the CFOA can avoid the local optimum of the PDV based on the judgment of smell concentration. The generating mechanisms of candidate PDVs based on the connection cloud model and IDC analysis are helpful to improve the search speed of the optimal PDV. In case 2, the above features were also observed. These indicate that the PP method using the CCMFOA is easy to determine the dangerous degree of debris flow disaster and more convenient for application than other ways. The CFOA model can speed up the searching rate of the PP method but may lead to the problem of the local optima. Therefore, the CCMFOA can get better search efficiency and higher precision of the optimal PDV and and fuzziness of the searching process and mea-sured indicators.

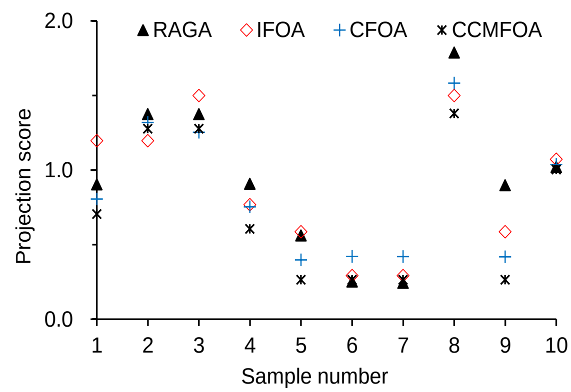

Figure 6. Results of project scores of samples for case 1.

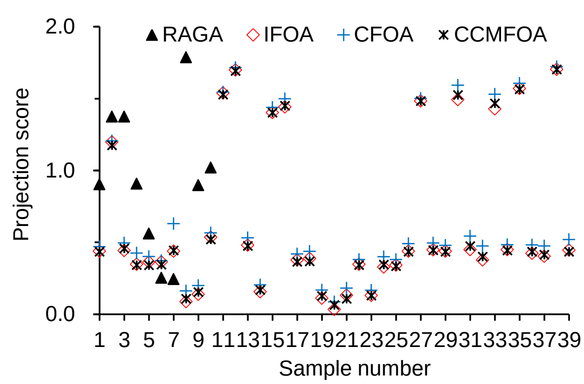

Figure 7. Results of project scores of samples for case 2.

Table 8. Optimal PDVs Obtained from Different Algorithms for Case 2

Algorithms	S_1	S_2	S_3	S_4	S_5	S_6	S_7
IFOA	0.088	0.662	0.097	0.247	0.008	0.417	0.556
CFOA	0.196	0.555	0.131	0.246	0.068	0.515	0.553
CCMFOA	0.144	0.661	0.020	0.261	0.045	0.435	0.532

The assessment of debris flow disasters involving numerous uncertain indicators is a complex problem of uncertainty. The case study suggests that the CCMFOA with proper global and local search capabilities can avoid some defects of the basic FOA. It has better efficiency and accuracy because it can depict the randomness and fuzziness of the optimal PDV and the foraging behaviors of the fruit fly swarm. It has the following benefits over other methods.

1) The conventional methods for assessing debris flow disasters generally need to construct the corresponding classification standard. Many uncertain indexes affect debris flow disasters, and the classification standard may vary with locations. It may restrict the application extent of these methods with the particular classification standard. So the CCMFOA-based PP method provides a fresh idea to analyze the debris flow disasters directly through measured data without the rating standard.

2) The CCMFOA can memorize a possible optimal PDV by the expectation *Ex*, and depict the individual's search radius and learning stability by the entropy *En* and the hyper entropy *He*, respectively. These characteristics can enhance the algorithm to get the optimal PDV from elite individuals and avoid limiting the normal distribution in the normal cloud model.

3) Candidate PDVs screened with the IDC rules of set pair analysis enable the optimization process of the algorithm to be more streamlined with the mechanism "picks the best of the best". Namely, the candidate PDV produced randomly can be screened before the complex calculation of the PP method according to the connection degree between the candidate PDV and the optimal PDV obtained from the latest optimization.

4) The proposed PP method using the CCMFOA overcomes the disadvantage of knowledge acquisition and the black-box effect in the neural network method. It can directly depict the relationship between the indicators and the degree of debris flow disasters.

5. Conclusions

Debris flow often poses potential threats to engineering construction activities and the residents in the debris flow-prone areas. The assessment of debris flow disasters is a nonlinear problem of multiple uncertainties. Hence, its rational evaluation is critical for risk management prevention and mitigation work in mountain areas. However, most of the previous methods for assessing the dangerous degree of debris flow at the regional scale almost cannot reflect the structural characteristics of the original non-normal data. Conventional projection pursuit methods can deal with this problem but are not powerful enough to simultaneously describe the fuzziness and randomness of the optimal PDV. Hence, the novel PP method using the CCMFOA is presented here to depict the multiple uncertainties of the PDV and overcome the above shortcomings of the traditional assessment methods of debris flow disasters. Two illustrative examples and compaisons further confirmed the validity and reliability of the proposed method. Some conclusions are obtained as follows.

1) Debris flow disasters involve various uncertain indexes, and there lacks a uniform classification standard of dangerous degree for debris flow disasters. It may restrict the application extent of these methods of the particular classification standard. So the CCMFOA-based PP method without the rating standard provides a refreshing idea to examine the debris flow disasters directly through measured data.

2) Compared with other FOAs, the CCMFOA can remember the recently obtained superior projection directions using the expectation *Ex* and depict the randomness and fuzziness of an individual's search radius and learning stability by the entropy, *En*, and the hyper entropy *He*, respectively. So the proposed method can ensure the reliability of the optimal PDV obtained from elite individuals. Moreover, it can provide a more accurate PDV with better optimization efficiency for the PP method. It utilizes the connection cloud model to produce the candidate PDV around the latest optimal PDV according to the mechanism "Picks the best of the best". Namely, the analysis of the IDC relationship between the candidate PDV and the optimal PDV obtained from the latest optimization iteration is carried out to screen the candidate PDV before the complex computation of the projection score.

3) Case studies indicate that the CCMFOA-based PP method is more reasonable and feasible than the neural network method. The proposed method can fully depict the structure and information of non-normal distribution data of samples in one-dimensional space and the randomness and fuzziness characteristics of the PDV. Meanwhile, it can compensate for the defects of the neural network method that the results rely on the sample data for training and validation. This proposed method without rating standards provides an alternative way to assess the dangerous degree of debris flow under multiple uncertainties. In addition, the proposed method overcomes the defect of a fixed search scope in the original FOA or other improved FOAs. And the computational projection rate of the way presented here is faster than that of the original FOA or other improved FOAs. This method with high convergence accuracy will provide a scientific basis for management and decision-making.

4) Due to the complexity of debris flow hazards under multiple uncertainties, it is hard to apply the basic FOA to find the optimal PDV of the PP method. Application and comparisons of examples have verified the validity and capability of the proposed PP method to assess debris flow disasters. Although the CCMFOA can provide more accurate PDV for the PP method relative to other FOAs, how to produce the excellent original PDV still needs to be further investigated to improve the proposed method's stability in the future.

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